Power Quality Disturbances Analysis and Detection using Discrete and Continuous wavelet transforms

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Article Info

Article history:

Received Nov 12th, 2014
Accepted Nov 19th, 2014
Publication Nov 22th , 2014

Keyword:

Power quality issues,
discrete wavelet transform,
Continuous wavelet transforms.

ABSTRACT

This paper discusses power quality Disturbances analysis and detection using discrete wavelet transform (DWT) and Continuous wavelet transform (CWT). Two power quality disturbances, Sag and Swell is analyzed in this paper. Results are carried out in MATLAB/Simulink Environment.

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I. Introduction

Scenario has changed a lot. With the increase of size and capacity, power systems have become complex leading to reduced reliability. But the development of electronics, electrical device and appliances has become more and more sophisticated and they demand uninterrupted and conditioned power. In this ever changing power scenario, quality assurance of electric power has also been affected. It demands a deep research and study on the subject 'Electric Power Quality. 'Institute of Electrical and Electronic Engineers (IEEE) Standard IEEE1100 defines power quality as the concept of powering and grounding sensitive electronic equipment in a manner suitable for the equipment. A simpler definition is stated as below. Power quality is a set of electrical boundaries that allows a piece of equipment to function in its intended manner without significant loss of performance or life expectancy. Electric Power Quality (EPQ) is a term that refers to maintaining the near sinusoidal waveform of power distribution bus voltages and currents at rated magnitude and frequency. Thus EPQ is often used to express voltage quality, current quality, reliability of service, quality of power supply, etc., Fundamental concept identifies the parameters and their degree of variation with respect to their rated magnitude which are the base reason for degradation of quality of electric power. Sources are the regions which causes the unwanted variation of those parameters. Effects of poor quality of power are the effects faced by the system and consumer equipment after the occurrence of different disturbances [1], [2]. In modeling and analysis, attempts are taken to configure the disturbance, its occurrence, sources and effect; mainly based on the mathematical background. For monitoring of EPQ, constant measurement and instrumentation of the electric parameters are necessary. Complete solution, i.e. delivery of pure power to the consumer side is practically impossible. Our target is to minimize the probability of occurrence of disturbances and to reduce the effects of EPQ problems. To ensure uninterrupted

and quality power has thus become a point of importance for the power producers. Quality degradation n of electric power is mainly occurred due to power line disturbances such as impulses, notches, voltage sag and swell, voltage and current unbalances, momentary interruption and harmonic distortions. The other major contributors to poor power quality are harmonics and reactive power. Solid state control of ac power using high speed switches are the main source of harmonics whereas different non-linear loads contribute to excessive drawl of reactive power from supply.

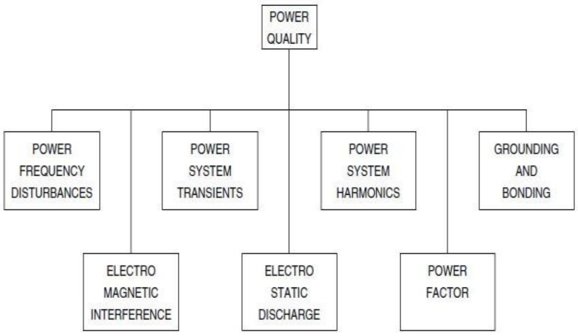

Fig.1 Power quality issues

Power frequency disturbances are low frequency phenomena that result in voltage sags or swells. These may be source or load generated due to faults or switching operations in a power system. Power system transients are fast, short duration events that produce distortions such as notching, ringing and impulse. Power system harmonics are low frequency phenomena characterized by waveform distortion, which introduces harmonic frequency components. Voltage and current harmonics have undesirable effects on power system operation and power system components. In some instances, interaction between the harmonics and the power system parameters(R-L-C) can cause harmonics to multiply with severe consequences [1], [5].

The subject of grounding and bonding is one of the more critical issues in power quality studies. Grounding is done for three reasons. The fundamental objective of grounding is safety. The second objective of grounding and bonding is to provide a low impedance path for the flow of fault current in case of a ground fault so that the protective device could isolate the faulted circuit from the power source. The third use of grounding is to create a ground reference plane for sensitive electrical equipment. This is known as the signal reference grounding (SFG) [6]-[9].Electromagnetic interference (EMI) refers to the interaction between electric and magnetic fields and sensitive electronic circuits and devices. EMI is pre-dominantly a high frequency phenomenon. Radio frequency interference (RFI) is the interaction between conducted or radiated radio frequency fields and sensitive data and communication equipment. It is convenient to include RFI in the category of EMI, but the two phenomena are distinct. Electrostatic discharge (ESD) is a very familiar and unpleasant occurrence. SD is harmful to electronic equipment causing malfunction and damage. Power factor is included for the sake of completing the power quality discussion.

II. Wavelet Transforms

Wavelet is a mathematical function used to divide continuous time signal into different scale components. Wavelet theory provided new method for decomposing a function or signal into various frequency components and then study each component with a resolution match to its scale. Translation and scaling is used to generate wavelets from a single basic wavelet. This single basic wavelet is called as mother wavelet. In wavelet analysis, we get details and approximations. The details are the low scale, high frequency components and the approximations are the high scale low frequency components. The strength of the wavelet analysis is its ability of representing signals in compact from and in many levels of resolution. Each scale component can then be studied with a resolution that matches its scale. Wavelet transform is one of the most frequently used algorithms to analyze power signal. It is the representation of a function by wavelets. Main feature of wavelets is oscillating and rapid decay to zero. It has an advantage of low cost, real calculation and possible hand held device implementation. It has an excellent time localization feature when a transient or high frequency disturbance occurs in a normal signal. It is appropriate for non-stationary and non-periodic wide band signal. It is capable of revealing aspects of data that other signal analysis techniques miss. Wavelets are effective for analysis of textures recorded with different resolution.

There are two types of wavelet transforms. They are discrete wavelet transform (DWT) and continuous wavelet transform (CWT).The prime difference between discrete wavelet transform and continuous wavelet transform is that discrete wavelet transform use an explicit subset of scale and translation values and continuous wavelet transform uses all possible scale and translation. The discrete wavelet transform (DWT) is a linear transformation that operates on a data vector whose length is an integer power of two, transforming it into a numerically different vector of the same length. It is a tool that separates data into different frequency components, and then studies each component with resolution matched to its scale.

A. *Discrete Wavelet Transform*

The signal is passed through a series of low pass and high pass filter to generate discrete wavelet transform. To extend the frequency resolution, decomposition of signal is done repeatedly and signal can be realized into two lower frequency ranges. This process is known as multi-resolution analysis. Approximate coefficients A1 (n) and detail

coefficients D1 (n) obtained after passing the signal through low pass and high pass filters, at level 1.

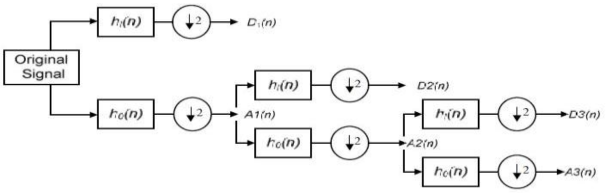

Fig.2 Signal three level decomposition using MRA

Approximation coefficients A1 (n) are down sampled further with high and low pass filters as shown in the figure above. The approximate coefficients A2 (n) are then filtered again to obtain the next level of coefficients. This filtering operation progresses in this way. At each level in the below figure, the signal is decomposed into low and high frequencies. Due to the decomposition process the input signal must be a multiple of 2n where n is the number of levels.

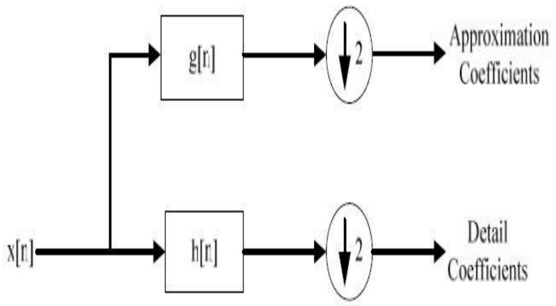

Fig.3 Block diagram of filter analysis

The discrete wavelet transform (DWT) command performs single-level one-dimensional wavelet decomposition with respect to particular wavelet. It is even faster than fast Fourier transform (FFT). It is easier to implement than continuous wavelet transform (CWT). DWT is a linear transformation that operates on a data vector whose length is an integer power of two, transforming it into a numerically different vector of the same length. The signal is passed through a series of low and high pass filters to generate discrete wavelet transform. DWT uses the discrete values of the signal in time domain.

Mathematically the expression for DWT is:

$$\varphi_{a,b}(t) = \frac{1}{\sqrt{a_0^m}}\left(\frac{t - nb_0 a_0^m}{a_0^m}\right) \qquad (1)$$

Where m and n are the integers which control the wavelet dilation and translation respectively.a0 is a fixed dilation step parameter which would be always greater than one and b0 is the position parameter, its value should be more than zero. It down samples signal into detailed and approximate coefficients. Starting from a signal S, these two sets of coefficients i.e. CA1 and CB1 are computed. These vectors are obtained by convolving S with the low pass filter Lo_D for approximation and with the high pass filter Hi_D for detail.

The main feature of DWT is multi-scale representation of function. By using wavelets, given function can be analyzed at various levels of resolution. It is also invertible and can be orthogonal.

The 1-D wavelet transform is given by:

$$W_f(a,b) = \int_{-\infty}^{\infty} x(t)\varphi_{a,b}(t)dt \qquad (2)$$

B. Continuous Wavelet Transform

CWT type is usually preferred for signal analysis, feature extraction and detection tasks. CWT uses a time window function that changes with frequency.

The CWT of a continuous signal is expressed in terms of wavelet coefficients, for different values of scaling factor 'a' and translation factor 'b' as:

$$CWT_x(a,b) = \int_{-\infty}^{\infty} x(t)\varphi_{a,b}^*(t)dt \qquad (3)$$

Where,

$$\varphi_{a,b}(t) = \frac{1}{\sqrt{a}}\varphi\left(\frac{t-b}{a}\right) \qquad (4)$$

x (t) is the signal to be analyzed,
Ψa,b (t) is the mother wavelet,
'a' is scaling parameter and 'b' is translation parameter.
The factor a-1/2 is for energy normalization across the different scales. The term mother implies that the functions with different region of support that are used in the transformation process are derived from one main function, or the mother wavelet. In other words, the mother wavelet is a prototype for generating the other window functions.

Each mother wavelet has its own characteristics and will project different types of resolutions. The mother wavelets selected will serve as prototypes for all windows in the process. All the windows that are used are dilated and shifted versions of the mother wavelet functions. There are different types of mother wavelet, namely, the Morlet, Meyer, Gaussian, Mexican hat, Haar and Daubechies wavelets. The Morlet wavelet is commonly used for signal analysis and therefore it is used for analysis of power disturbances. The main disadvantage of CWT is its redundancy of using large number of scales resulting in a significant computational overhead.

III. Simulation Results

The results for both sag and swell using the transforms mentioned above are shown below.

A. Sag-DWT

The results for sag using different wavelets such as bior, cgau, cmor, colf, db, dmey etc... For different coefficients such as db2, db3 etc., are shown below.

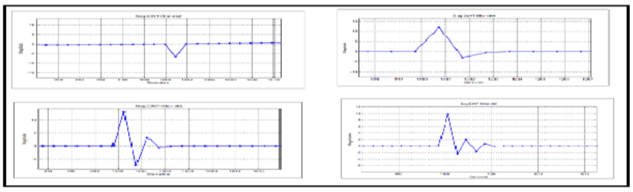

Fig.4 Curves showing variation in different wavelet coefficients such as db2, db4, db6, db8 for Bior wavelet

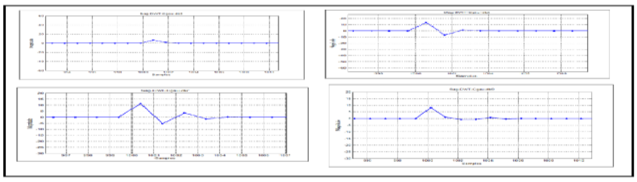

Fig.5 Curves showing variation in different wavelet coefficients such as db3, db5, db7, db9 for Cgau wavelet

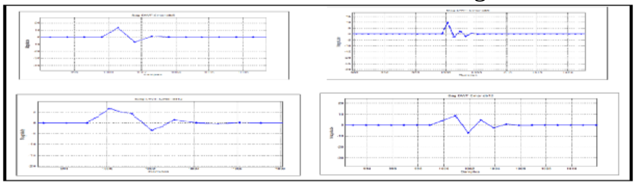

Fig.6 Curves showing variation in different wavelet coefficients such as db6, db8, db10, db12 for Cmor wavelet

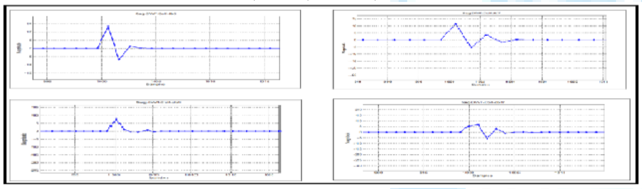

Fig.7 Curves showing variation in different wavelet coefficients such as db5, db7, db9, db11 for Colf wavelet

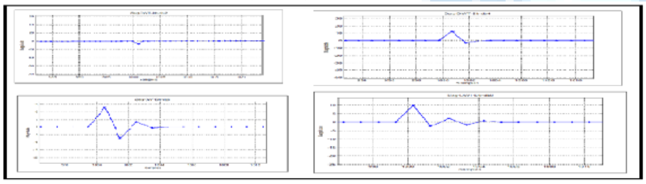

Fig.8 Curves showing variation in different wavelet coefficients such as db2, db4, db6, db8 for Db wavelet

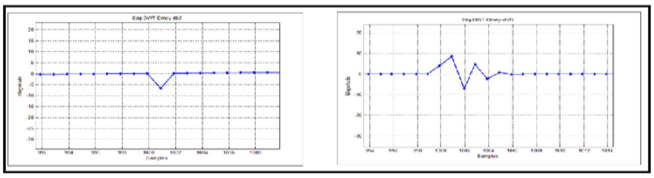

Fig.9 Curves showing variation in different wavelet coefficients such as db2, db12 for Dmey wavelet

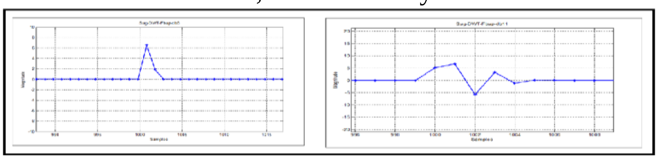

Fig.10 Curves showing variation in different wavelet coefficients such as db3, db11 for Fbap wavelet

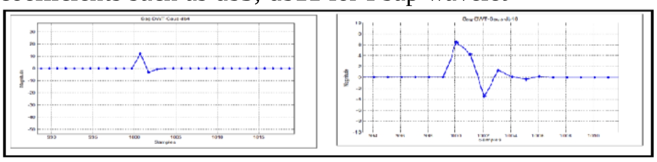

Fig.11 Curves showing variation in different wavelet coefficients such as db4, db10 for Gauss wavelet

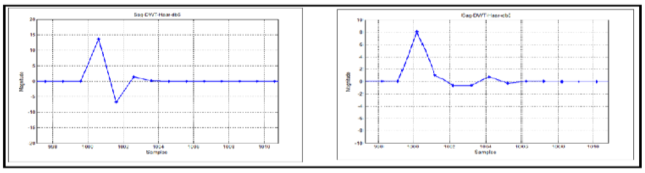

Fig.12 Curves showing variation in different wavelet coefficients such as db5, db9 for Haar wavelet

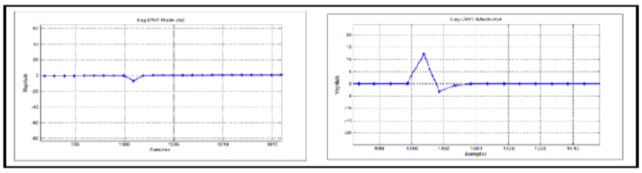

Fig.13 Curves showing variation in different wavelet coefficients such as db2, db4 for Mexh wavelet

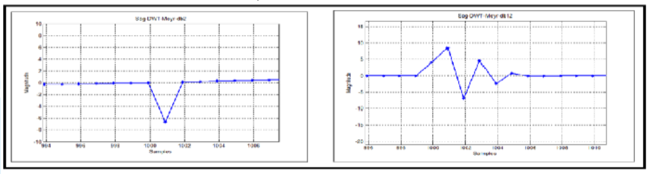

Fig.14 Curves showing variation in different wavelet coefficients such as db2, db12 for Meyr wavelet

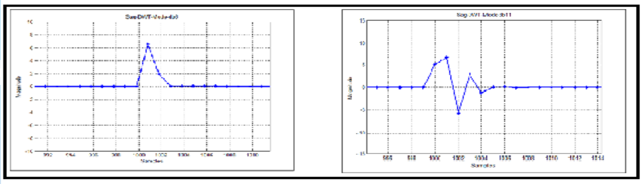

Fig.15 Curves showing variation in different wavelet coefficients such as db3, db11 for Mode wavelet

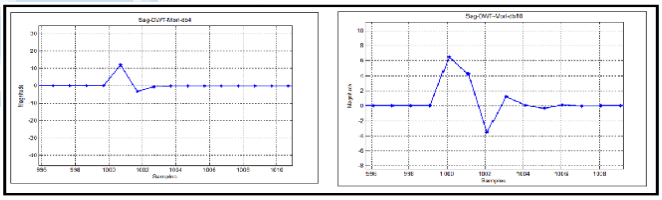

Fig.16 Curves showing variation in different wavelet coefficients such as db4, db10 for Morl wavelet

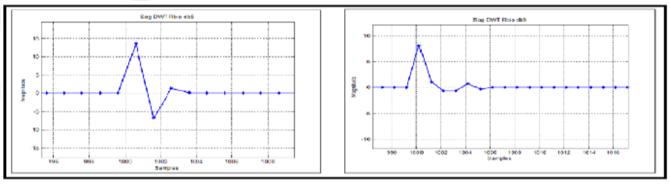

Fig.17 Curves showing variation in different wavelet coefficients such as db5, db9 for Rbio wavelet

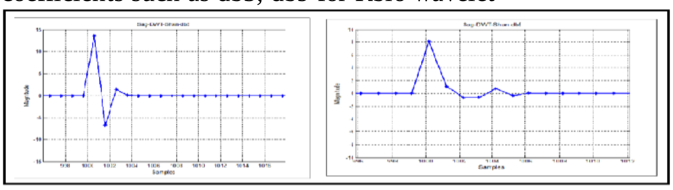

Fig.18 Curves showing variation in different wavelet coefficients such as db5, db9 for Shan wavelet

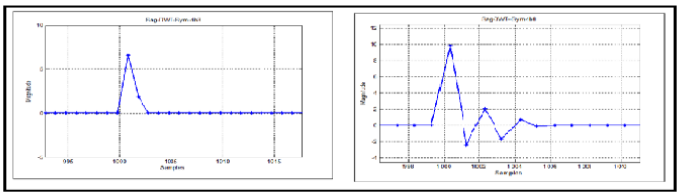

Fig.19 Curves showing variation in different wavelet coefficients such as db3, db8 for Sym wavelet

B. Sag-CWT

The results for sag using different wavelets such as dmey, meyr, morl, haar etc... are shown below.

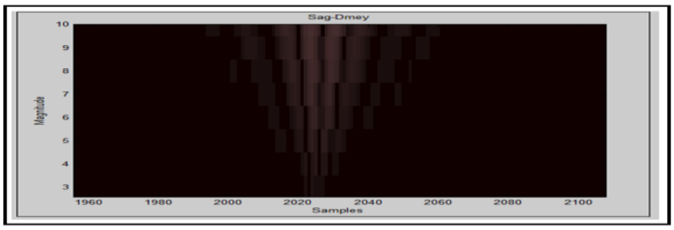

Fig.20 Curves showing variation for Dmey wavelet

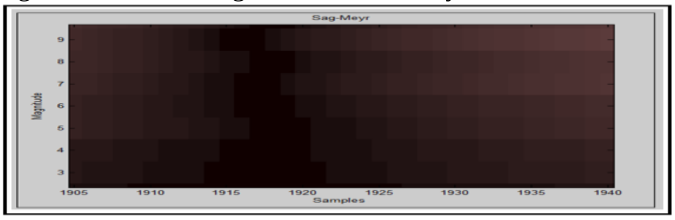

Fig.21 Curves showing variation for Meyr wavelet

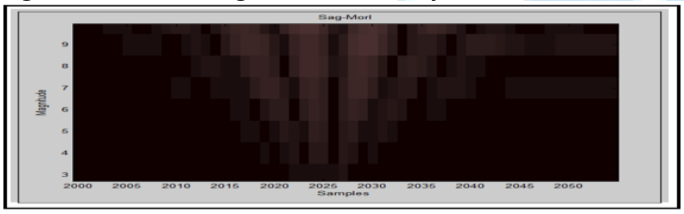

Fig.22 Curves showing variation for Morl wavelet

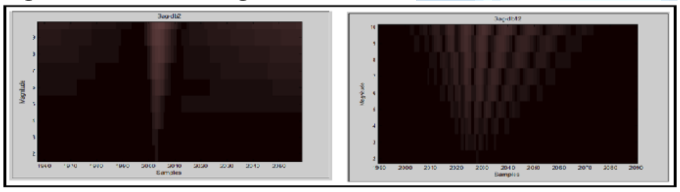

Fig.23 Curves showing variation for Db wavelet

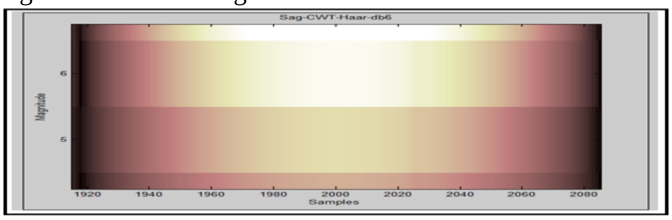

Fig.24 Curves showing variation for Haar wavelet

C. Swell-DWT

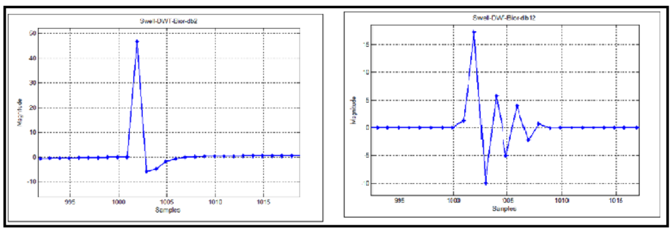

Fig.25 Curves showing variation in different wavelet coefficients such as db2, db12 for Bior wavelet

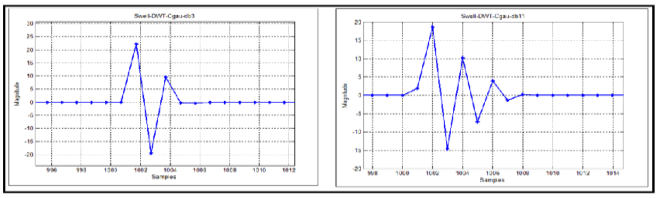

Fig.26 Curves showing variation in different wavelet coefficients such as db3, db11 for Cgau wavelet

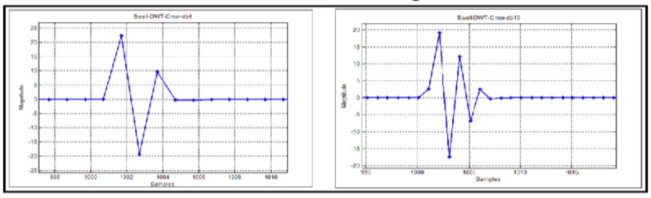

Fig.27 Curves showing variation in different wavelet coefficients such as db4, db10 for Cmor wavelet

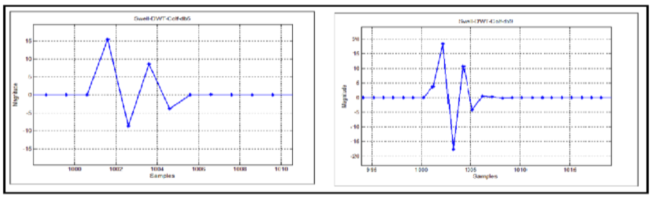

Fig.28 Curves showing variation in different wavelet coefficients such as db5, db9 for Colf wavelet

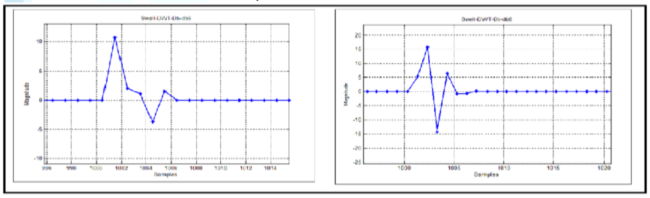

Fig.29 Curves showing variation in different wavelet coefficients such as db6, db8 for Db wavelet

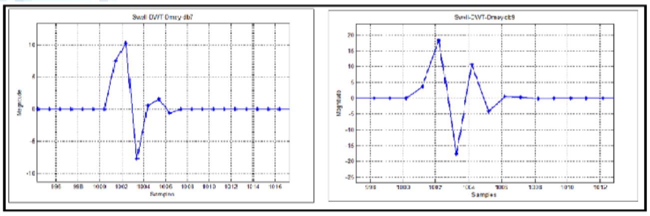

Fig.30 Curves showing variation in different wavelet coefficients such as db7, db9 for Dmey wavelet

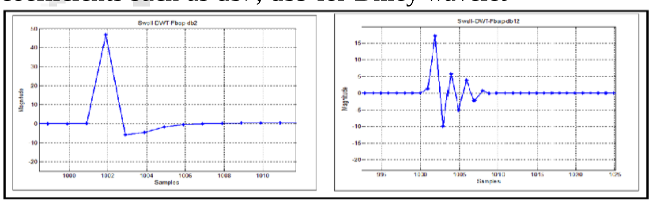

Fig.31 Curves showing variation in different wavelet coefficients such as db2, db12 for Fbap wavelet

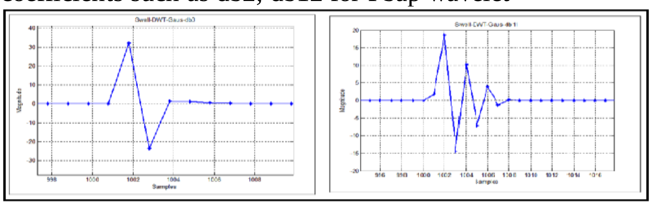

Fig.32 Curves showing variation in different wavelet coefficients such as db3, db11 for Gauss wavelet

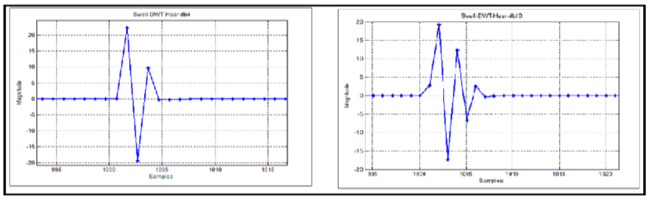

Fig.33 Curves showing variation in different wavelet coefficients such as db4, db10 for Haar wavelet

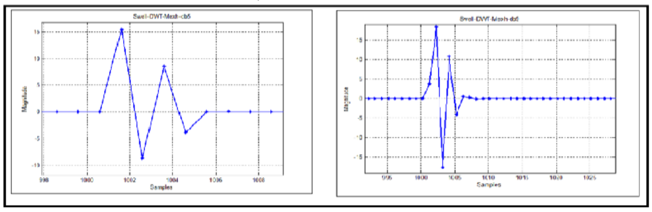

Fig.34 Curves showing variation in different wavelet coefficients such as db5, db9 for Mexh wavelet

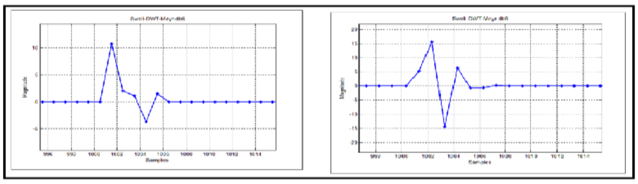

Fig.35 Curves showing variation in different wavelet coefficients such as db6, db8 for Meyr wavelet

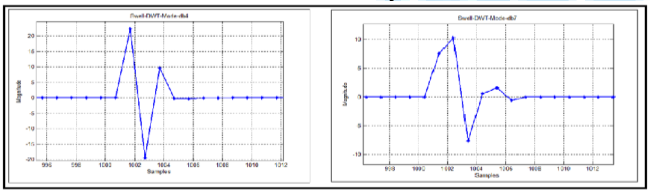

Fig.36 Curves showing variation in different wavelet coefficients such as db4, db7 for Mode wavelet

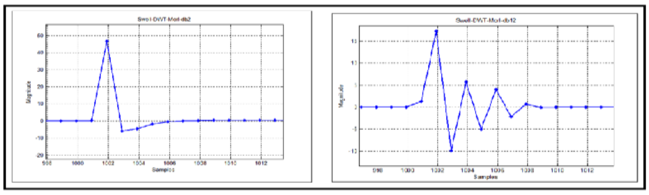

Fig.37 Curves showing variation in different wavelet coefficients such as db2, db12 for Morl wavelet

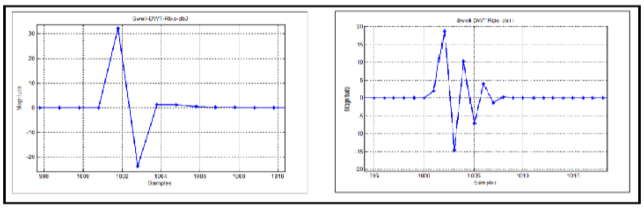

Fig.38 Curves showing variation in different wavelet coefficients such as db3, db11 for Rbio wavelet.

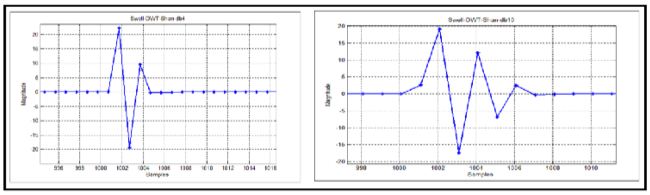

Fig.39 Curves showing variation in different wavelet coefficients such as db4, db10 for Shan wavelet.

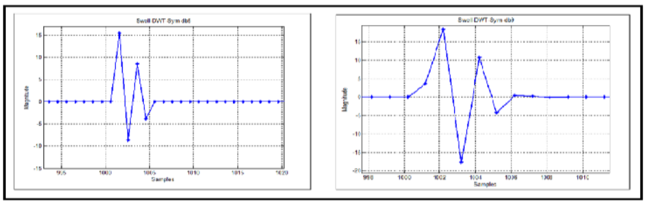

Fig.40 Curves showing variation in different wavelet coefficients such as db5, db9 for Sym wavelet.

D. Swell-CWT

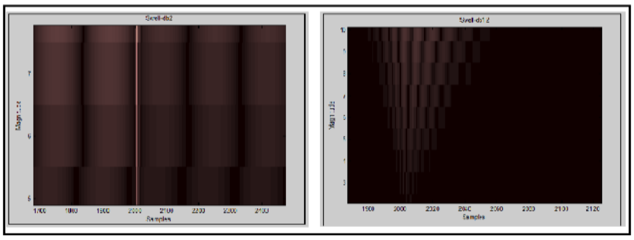

Fig.41 Curves showing variation for Db wavelet

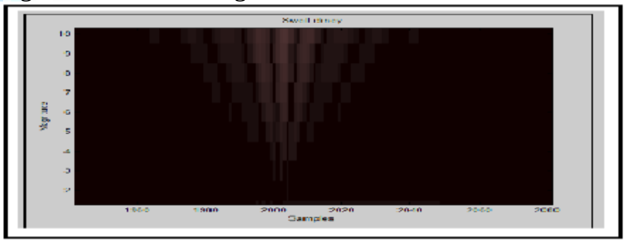

Fig.42 Curves showing variation for Dmey wavelet

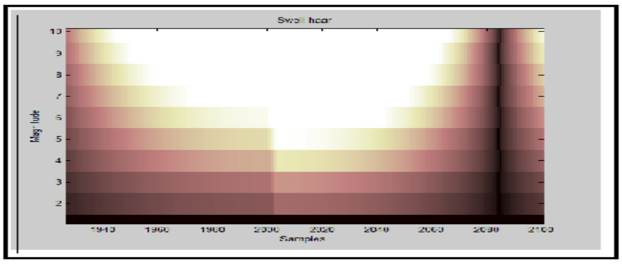

Fig.43 Curves showing variation for Haar wavelet

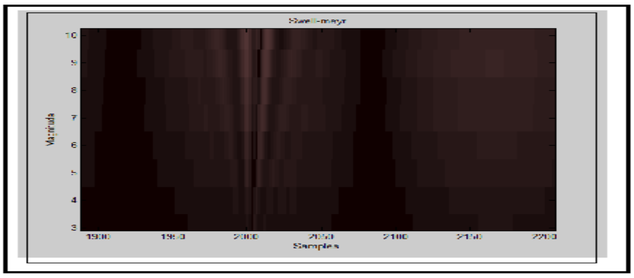

Fig.44 Curves showing variation for Meyr wavelet

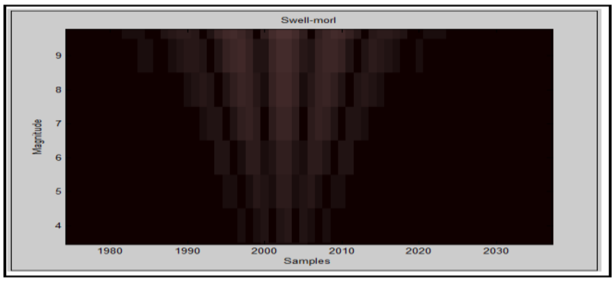

Fig.45 Curves showing variation for Morl wavelet

IV. Comparisons

The comparison between different coefficients of sag between different wavelets is shown below.

Table 1: Coefficients of DWT for Sag

Wavelet Name	Coefficient Values	
	db2	db12
Bior	0.006198,-6.703,0.133	8.484,-7.017,4.584
Cgau	0.006198,-6.703,0.133	8.484,-7.017,4.584
Cmor	0.006198,-6.703,0.133	8.484,-7.017,4.584
Colf	0.006198,-6.703,0.133	8.484,-7.017,4.584
Db	0.006198,-6.703,0.133	8.484,-7.017,4.584
Dmey	0.006198,-6.703,0.133	8.484,-7.017,4.584
Fbap	0.006198,-6.703,0.133	8.484,-7.017,4.584
Gaus	0.006198,-6.703,0.133	8.484,-7.017,4.584
Haar	0.006198,-6.703,0.133	8.484,-7.017,4.584
Mexh	0.006198,-6.703,0.133	8.484,-7.017,4.584
Meyr	0.006198,-6.703,0.133	8.484,-7.017,4.584
Mode	0.006198,-6.703,0.133	8.484,-7.017,4.584
Morl	0.006198,-6.703,0.133	8.484,-7.017,4.584
Rbio	0.006198,-6.703,0.133	8.484,-7.017,4.584
Shan	0.006198,-6.703,0.133	8.484,-7.017,4.584
Sym	0.006198,-6.703,0.133	8.484,-7.017,4.584

The comparisons between different coefficients of swell between different wavelets are shown below in table 2.

Table 2: Coefficients of DWT for Swell

Wavelet Name	Coefficient Values	
	db2	db12
Bior	46.78,-5.775,-0.5126	17.21,-9.933,5.76
Cgau	46.78,-5.775,-0.5126	17.21,-9.933,5.76
Cmor	46.78,-5.775,-0.5126	17.21,-9.933,5.76
Colf	46.78,-5.775,-0.5126	17.21,-9.933,5.76
Db	46.78,-5.775,-0.5126	17.21,-9.933,5.76
Dmey	46.78,-5.775,-0.5126	17.21,-9.933,5.76
Fbap	46.78,-5.775,-0.5126	17.21,-9.933,5.76
Gaus	46.78,-5.775,-0.5126	17.21,-9.933,5.76
Haar	46.78,-5.775,-0.5126	17.21,-9.933,5.76
Mexh	46.78,-5.775,-0.5126	17.21,-9.933,5.76
Meyr	46.78,-5.775,-0.5126	17.21,-9.933,5.76
Mode	46.78,-5.775,-0.5126	17.21,-9.933,5.76
Morl	46.78,-5.775,-0.5126	17.21,-9.933,5.76
Rbio	46.78,-5.775,-0.5126	17.21,-9.933,5.76
Shan	46.78,-5.775,-0.5126	17.21,-9.933,5.76
Sym	46.78,-5.775,-0.5126	17.21,-9.933,5.76

The comparison between different coefficients of sag between different wavelets is shown below in tables 3 and 4.

Table 3: Coefficients of CWT for Sag

Wavelet Name		Values	
		Index	RGB
Db	db2	2	0.101,0.0528,0.0528
	db12	38	0.494,0.321,0.321
Dmey		95	0.772,0.53,0.512
Haar		186	0.922,0.922,0.741
Meyr		148	0.859,0.782,0.636
Morl		108	0.795,0.604,0.546

Table 4: Coefficients of CWT for Swell

Wavelet Name		Values	
		Index	RGB
Db	db2	3	0.129,0.0747,0.0747
	db12	6	0.19,0.118,0.118
Dmey		5	0.172,0.106,0.106
Haar		162	0.885,0.846,0.67
Meyr		10	0.249,0.158,0.158
Morl		9	0.236,0.149,0.149

V. Conclusion

The Voltage sag and swell is analyzed using both DWT and CWT. The variations and results are compared in this paper in detail. Under each case different coefficients are taken for analysis.

References

[1] Sudipta Nath,Arindam Dey and Abhijit Chakrabarti, Detection of Power Quality Disturbances using Wavelet Transform, World Academy of Science, Engineering and Technology,Vol:3 2009-01-20.

[2] Bhavna Jain, Shailendra Jain and R.K.Nema, Investigations on Power Quality Disturbances Using Discrete Wavelet Transform, International Journal of Electrical, Electronics and Computer Engineering 2(2): 47-53(2013).

[3] Wavelet Toolbox User's guide by The Math Works.

[4] A Really Friendly Guide to Wavelets- © C.Valens,1999

[5] M.Sushama, Dr.G.Tulasi RamDas, DrA. Jaya Laxmi (2007), "Mitigation of Voltage Sags with Dynamic Voltage Restorer Using Wavelets" presented at the international Conference "RACE2007" during MAR 22nd-24th.

[6] C.Sidney Bums, Ramesh A.Gopinath, Haitao Guo (1998), "Introduction to Wavelets and Wavelet Transforms".

[7] M.Misiti, Y. Misiti, G. Oppenheim and J.-M Poggi (2006), Wavelet Toolbox For Use With Matlab: user's guide version 3, Mathworks Inc.

[8] Robi Polikar, 'The Wavelet Tutorial', 136 Rowan Hall, Department of Electrical and Computer Engineering, Rowan University, Glassboro, NJ 08028, June 1996.

[9] S. Santoso, E.J. Powers, and W.M. Grady, "Electric power quality disturbance detection using wavelet transform analysis," in Proceedings of the IEEE-SP International Symposium on Time- Frequency and Time-Scale Analysis, Philadelphia, PA,Oct. 25-28, 1994, pp. 166-169.

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